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Review article

An efficient probabilistic routing scheme based on game theory in opportunistic networks

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ABSTRACT

Routing is one of the most challenging problems in opportunistic networks (OppNets) because of the intermittence of the network connection. To address the issue, many routing schemes have been proposed, however, most of them assume that nodes are willing to forward messages for others. In fact, due to limited resources and poor social relations, nodes in OppNets may be selfish and not reluctant to participate in message forwarding. To tackle this issue, in this paper, we propose a Probabilistic Routing scheme based on Game Theory (PRGT) to stimulate cooperation among selfish nodes. Firstly, we introduce virtual money to buy the message for gaining more profits. Then, according to the historical meeting records among different nodes, we establish a Markov-based probability prediction model, in which the message carrier selects a node with higher probability of encountering the destination node as the relay node. Finally, a game theory approach is employed to simulate trading price for message forwarding. The simulation results demonstrate that our proposed routing scheme can effectively improve the delivery rate of messages and reduce network latency.

1. Introduction

OppNets are a subset of Delay Tolerant Networks (DTNs) where an end-to-end path between the source node and the destination node may not exist [1–4]. In OppNets, due to the randomness of intermittent connectivity and uncertainty of network topology, traditional routing algorithms based on TCP/IP are not applicable. Hence, nodes transmit messages with a store-carry-forward mechanism and messages can be transmitted to the destination nodes through relay nodes [5–8]. Obviously, such communication method relies heavily on the cooperation and interaction among nodes [9,10].

In fact, most of the nodes in OppNets may be selfish [11–14]. Thus, a node may be reluctant to forward messages for others due to limited resources, such as energy, buffer and so on, which is not conducive to improve the performance of the whole network. Therefore, an effective incentive scheme should be designed to promote cooperation among selfish nodes in OppNets.

In recent years, many incentive routing schemes have been proposed for wireless networks [15–17]. However, most of the existing incentive schemes are based on an end-to-end connection or a fixed path, and these schemes are not suitable for OppNets. Thus, it is still an meaningful problem to design incentive routing schemes in OppNets.

In this paper, an incentive probabilistic routing scheme for transmitting messages in OppNets is proposed. Firstly, to predict the probability of message forwarding, we establish a first-order Markov process according to the historical meeting records of nodes. Next, in order to inhibit the selfishness of relay nodes and ensure relay nodes participate in message forwarding, we employ game theoretic approach to promote the cooperation among nodes. In this process, we regard every message as a commodity. Each node has own virtual money and can make virtual money by selling commodities (messages) to others. If a node does not participate in message forwarding, then it will not have enough money to get more profits. To further promote the cooperation among nodes, if a message is received by the destination node, then all relay nodes participating in message forwarding will be rewarded. Based

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on this mechanism, both selfish nodes and normal nodes are willing to participate in the message forwarding, which has a great impact on improving the network performance. Our main contributions of this paper are as follows:

- We develop a probabilistic prediction model based on the Markov chain. In this model, we utilize the nodes' historical encounter records to evaluate the encounter probabilities among different nodes at the next moment. On this basis, we establish a state transition probability matrix, and the message carrier can choose a suitable relay node through this matrix.
- We analyze the selfishness of the nodes and establish a new method for computing the selfishness of the nodes. Besides, We also explain the reason of nodes' selfishness with our proposed bargain game scheme, that is, in the process of message forwarding, the relay nodes not only fail to make profits, but also damage its own benefits. Therefore, it is important to take an incentive method for relay nodes to participate in message forwarding.
- We simulate the forwarding process of messages as a bargaining process to stimulate cooperation between selfish nodes. In addition, we prove that, if both sides of the transaction use our proposed bargain game model, there exists a sub-game perfect Nash equilibrium in the bargain game, which means that a node can not obtain more profits by unilaterally proposing a trading scheme. Thus, cooperation is the best choice for each selfish node in the network.
- Compared to existing routing algorithms such as Epidemic [18], Prophet [19] and SprayAndWait [20], extensive simulation results validate the effectiveness of our model and algorithm. At the same time, the simulation results also show that our proposed routing algorithm can effectively promote the cooperation of selfish nodes, reduce network overhead and improve the delivery ratio.

The rest of this paper is organized as follows. In Section 2, we discuss some related works. In Section 3, we present system models. In Section 4, we present our designing routing scheme. In Section 5, we analyze the evaluation results about our proposed routing algorithm. Finally, we conclude our work and discuss future work in Section 6.

2. Related works

In OppNets, a desirable routing algorithm for opportunistic network can provide reliable message transmission, even when the network connection is intermittent or an end-to-end path does not exist. Therefore, how to design an efficient routing algorithm is critical. To address this problem, many existing routing algorithms can be divided into two categories, according to the incentive measures, namely non-incentive routing algorithms and incentive routing algorithms.

2.1. Non-incentive routing algorithms

Non-incentive routing algorithms usually build on the assumption that all nodes in the networks are cooperative and willing to participate in message forwarding. For example, in Tan et al. [21], SAUCeR uses cooperative retransmission to improve Quality of Service. If a high-priority node pH does not forward the message m to the destination node successfully, then the low-priority nodes, who have the message m from the node PH, will be considered as suitable relay nodes by SOSS or RR. In HFS [22], each node has a gathering place called 'hotspot' (where the nodes visit frequently some locations, for instance, shops, bus stations, workplaces, home and so on). When a node enters into its own 'hotspot', it distributes the message to all nodes travelling to other communities with a flooding scheme. To complete the forwarding of messages, in VGA [23], the source node utilizes On-demand routing or transitive closure routing approach to detect a path to the destination node. Such routing schemes [24–26] are closely dependent on the location information of the nodes.

In addition, there are some non-incentive routing algorithms considering social properties such as reputation, centrality, interest, or similarity and so on. In SAROS [27], a node uses reputation and trust mechanism to judge the correctness of a message to avoid the spread of error messages. Pass [28] combines the position similarity and social similarity using the fuzzy inference method to promote the network performance. In Pass, routing is based on a $f - value$, the larger the $f - value$ of a node, the more suitable it is to be a relay node. In Kim and Kim [29], it adopts the centralities such as percolation, closeness, betweenness and degree to forward messages. Each node forwards messages only through hub nodes selected by the centralities as the relay node. M-DART [30] uses the multi-path data forwarding strategy to complete message forwarding. In M-DART, the neighbour node, which shares the longest address prefix with the destination, will be selected as the relay node. If there are multiple neighbors sharing the longest address prefix, the node will select the one with the lowest route cost. In [31–34], a relay node is selected as the destination node by the common interest and social-aware between nodes.

Compared with classic routing algorithms [18–20], these routing algorithms do not forward messages blindly, but select appropriate relay nodes by context information. However, they do not consider selfishness among nodes.

2.2. Incentive routing algorithms

The incentive routing algorithms assume that the nodes in OppNets are selfishness. Therefore, the incentive routing algorithms are more consistent with the scene in the real network.

There are some incentive algorithms based on the trust of nodes. For example, in TRSS [35], a trust model is proposed to detect and purge the malicious and selfishness nodes. In this scheme, only trusted nodes' messages will be forwarded. So these malicious and selfish nodes have the incentives to behave well again. In Park [36], a cooperative relay routing algorithm based on trust-based incentive mechanism is proposed. According to the trust value of each relay node, it selects the most suitable relay node and pays a service-price for the relay node. TETO [37] employs highly trusted relay nodes to establish the routing scheme, which can minimize the possibility of a packet loss and guarantee the quality of message transmission. In this scheme, if a node is accused of message drop, then the trust value of the node will be decreased. Contrarily, if a node forwards messages to relay nodes, the trust value of the node will be increased.

In addition to trust-based incentive routing, some incentive routing algorithms are based on reputation, credit or game theoretic approach. For instance, IRONMAN [38] introduces an incentive scheme for opportunistic network that utilizes pre-existing social network information to detect and punish selfish nodes. In Liu [39], a reputation-based mechanism is designed to stimulate cooperation and prevent selfish behavior. In Xu et al. [40] a bargain game theory is employed for modeling the division of the difference value C for the reserve prices of buyer B and seller S. The buyer B and seller S solve the selfishness by sharing the cake C to promote the network performance.

Although the existing incentive algorithms consider the selfishness of nodes, it is hardly to quantify the selfishness of the nodes. In our work, we utilize node energy, buffer and social friendship to represent node selfishness, and propose a new metric to quantify node selfishness. Based on this, we utilize a game theory approach

这里没有考虑到 j有没有特质(比如距离dest更近/更频繁)；某些路由情况下，这些特质是否决定转发的关键!

to stimulate the cooperation between selfish nodes. Extensive simulation results show that our proposed routing scheme can effectively promote the cooperation of selfish nodes.

3. System models

This section focuses on the system model including network model, game theoretic model and probabilistic prediction model. In this paper, we make following assumptions: The movement of all nodes in the network follow a certain routine, for example, from home to workplace. Furthermore, there are no malicious and aggressive nodes in the network.

3.1. Network model

We consider a general opportunity network model, where an end-to end path does not always exist, and the nodes communicate with each other by a store-carry-forward mechanism. In the network, the initial energy of each node is E_s, and the buffer size is B_s. In addition, we regard every message as a commodity, and each node has some virtual money to buy commodities (messages). Meanwhile, nodes can make virtual money by selling commodities. Besides, there is a *Credit Clearance Center* (CCC), and each node has an account in it. The CCC is a server connected to the Internet, so that the nodes can access the CCC when they connects to the Internet [40]. The forwarding of each message will produce a receipt of the digital signature. Then both the message carrier and the relay node will submit the receipt to the CCC. Finally, when the destination node receives the message, it submits the confirmed information to the CCC. The CCC rewards all relay nodes participating in the message forwarding according to the digital signature. This means that the relay nodes have enough virtual money so that they can forward more messages to get more profits.

3.2. Game theoretic model

To maximize the cooperation of nodes and study the incentive measures, we model the message forwarding process as a bargain game.

In this paper, the message carrier is regarded as a seller *S*, and the relay is regarded as a buyer *B* [40]. Hence, there are two players including the seller *S* and the buyer *B* in the game. In the bargain game, both players need to reach a transaction price for every message in one round or multiple rounds. When a bargain game begins, the seller *S* firstly puts forward a deal, then the buyer *B* decides whether to accept it or not. Acceptance means the end of the game while rejection leads to the next round. In the next round, the buyer *B* puts forward another deal, then the seller *S* decides whether to accept it or not. Repeat this process until the transaction is completed.

3.3. Probabilistic prediction model based on Markov chain

We consider every node in the network as a place where a message can store. Thus,a forwarding process of a message m can be regarded as a binary set including a series of discrete positions P_i^m and time elements T_i^m. Based on this, we can define a transfer process of the messages m as follows:

$$PT = \left\{ (P_1^m, T_1^m), \cdots, \left(P_i^m, T_i^m\right), \cdots, (P_n^m, T_n^m) \right\} \tag{1}$$

where the tuple (P_i^m, T_i^m) indicates that at the T_i^m moment, the message m is in the position P_i^m, that is, at the T_i^m moment, the message m is in the node N_i.

Further, the process can be described by the Markov chain. The network nodes represent the set of states $S = \{1, 2, \cdots, i, \cdots, n\}$ where the state i denotes the message in the node N_i. The transfer probability matrix P where each element $p_{i,j} \in P$ denotes the transition probability between states i and j, that is, the probability that the message m is forwarded from node N_i to node N_j. Therefore, we can define a stochastic process $\{X(T), t \in T\}$, where for any time t and the state 1, 2, $\cdots$, i, j, $\cdots$, n, there is

$$\begin{aligned} p_{i,j} &= \{X(t+1) = j | X(t) = i, X(t-1) = i-1, \cdots, X(1) = 1\} \\ &= \{X(t+1) = j | X(t) = i\} \end{aligned} \tag{2}$$

To calculate the value of the $p_{i,j}$, we employ $c_{i,j}$ to denote the number of encountering between node N_i and N_j in a time period T. Thus, we can define encountering probability $p'_{i,j}$ between node N_i and N_j as follows:

$$p'_{i,j} = \frac{c_{i,j}}{\sum\limits_{r=1, r\neq i}^{n} c_{i,r}} \tag{3}$$

从i到j的概率;

一定时间T内
i到j的次数 / i到任何其他的次数

Besides, in the message forwarding, if a node N_j has received a message m, no matter which node forwards it, then the message m can not be forwarded to the node N_j again. In order to reveal this phenomenon, we utilize a forwarding factor ψ_j^m to describe it. ψ_j^m can be defined as follows:

$$\psi_j^m = \begin{cases} 0 & node\ N_j\ has\ received\ the\ message\ m \\ 1 & otherwise \end{cases} \tag{4}$$

Based on the above discussion, the probability $p_{i,j}$ that the message m can be transmitted from node N_i to node N_j (node N_i and node N_j are two different nodes) can be defined as

$$\begin{aligned} p_{i,j} &= p'_{i,j} \times \psi_j^m \\ &= \begin{cases} 0 & node\ N_j\ has\ received\ the\ message\ m \\ \dfrac{c_{i,j}}{\sum\limits_{r=1, r\neq i}^{n} c_{i,r}} & otherwise \end{cases} \end{aligned} \tag{5}$$

In addition, if a message is not transmitted from node N_i to node N_j, then the message is transmitted from node N_i to node N_i, in other words, the message is still in current state N_i. Therefore, $p_{i,i}$ can be defined as follows:

$$p_{i,i} = 1 - \sum_{j=1, j\neq i}^{n} p_{i,j} \tag{6}$$

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Thus, we can derive one step-state transition probability matrix P that a message is moved from one state to another, which is:

$$P = \begin{vmatrix} p_{1,1} & \dots & p_{1,j} & \dots & p_{1,n} \\ \vdots & & \vdots & & \vdots \\ p_{i,1} & \dots & p_{i,j} & \dots & p_{i,n} \\ \vdots & & \vdots & & \vdots \\ p_{n,1} & \dots & p_{n,j} & \dots & p_{nn} \end{vmatrix} \tag{7}$$

From the formula (7), we can get the probability of a message moving from one node to another. In the probabilistic prediction model, we only establish one step state transition matrix, which is mainly because the calculation of the state transition matrix is simpler and more practical than the two steps or multi-step state transition matrix.

4. Design and analysis of our proposed routing scheme

In this section, we present a detailed introduction of our proposed routing scheme, which includes three parts: analyze and compute the selfishness of nodes, bargaining game scheme and routing decision scheme.

4.1. Analyze and compute the Selfishness of nodes

Since the selfishness is related to the status and relationship of nodes, we divide the node's selfishness into two categories. One is associated with the residual energy and buffer of nodes, which we call it *Self-Centered Selfishness* (SCS). The other is to consider the social relations of nodes, which means the node is more willing to forward messages of their friends than those of no-friend. We call it *Social Selfishness* (SS). Next, we will introduce SCS and SS, respectively.

A. Self-Centered Selfishness: In OppNets, the energy and buffer of a node are limited. When a node's energy and buffer are insufficient, the node is more willing to forward his own messages rather than other messages. Hence, the percentage of remaining energy and buffer can be used to define the *Self-Centered Selfishness.*

$$SCS = (\alpha \cdot \frac{E_r(t)}{E_s} + \beta \cdot \frac{B_r(t)}{B_s} + 1)^{-1} \quad \boxed{1/2 \sim 1/1} \tag{8}$$

where $E_r(t)$ is the remaining energy of node r at time t. Similarly, $B_r(t)$ is the remaining buffer of node r at time t. α and β are the influence weights of energy and buffer on the node's SCS, respectively. In addition, $\alpha + \beta = 1$.

B. Social Selfishness: Social selfishness is a very common feature among nodes, which reflects whether a node is willing to participate in message forwarding or not. For most nodes, if a message is from his friend, then the node is very likely to forward the message. Therefore, we consider the social selfishness of nodes and the relationship among nodes is a certain correlation, the closer the node is, the less the social selfishness and the more likely to forward the message. In Bulut and Szymanski [41], $w_{i,j}$ is used to represent a direct friend relationship. $w_{i,j}$ is defined as follows:

$$\begin{aligned} w_{i,j} &= \frac{T}{\int_{t=0}^{T} f(t)dt} \\ &= \frac{2T}{\sum_{x=1}^{n} t_{inter,x}^2} \end{aligned} \tag{9}$$

where $f(t)$ denotes the remaining time from the present time t to the next encounter time t_{next}. If nodes N_i and N_j contact with each other at time t, then $f(t) = 0$; otherwise, $f(t) = t_{next} - t$. $t_{inter,x}$ is the $x - th$ time interval within a time period T.

In addition, the social selfishness of a node is also related to the number of messages that the node forward for others in a time period T. The more messages the node forwards, the smaller the selfishness of the node is. We utilize $Q_{tot,i}$ to indicate the total number of messages that the node N_i forwards, accordingly, $Q_{oth,i}$ indicates the total number of messages that the node N_i forwards for others in a time period T. More formally, we define *Social Selfishness* as follows:

$$\begin{aligned} SS &= k \cdot \frac{1}{w_{i,j}} \cdot (1 - \frac{Q_{oth,i}}{Q_{tot,i}+1}) \\ &= k \cdot \frac{\sum_{x=1}^{n} t_{inter,x}^2}{2T} \cdot (1 - \frac{Q_{oth,i}}{Q_{tot,i}+1}) \end{aligned} \tag{10}$$

where $k \in (0, 1)$ denotes a social selfishness factor of nodes. Obviously, at any time, both *Self-Centered Selfishness* and *Social Selfishness* have an impact on the message forwarding. Here, a new selfishness metric $SM_{i,j}$ between node N_i and node N_j is introduced by

$$SM_{i,j} = \phi \log_2(SCS + 1) + \varphi \log_2(SS + 1) \tag{11}$$

where ϕ, $\varphi \in (0, 1)$ denote the influence weights of SCS and SS on the node's selfishness, respectively.

4.2. Bargaining game scheme

In this subsection, we firstly define some utility functions of the game theory model. Then, based on these functions, we explain the reason for the selfishness of the nodes, and find out a balance point of trading price. Finally, an incentive mechanism is introduced.

As we have mentioned in Section 3.2, in our bargain game, the carrier is regarded as a seller S, and the relay is regarded as a buyer B. In the process of a message transmission, if the buyer B and seller S reach a purchase price z of the message m in round r, then the utility of the seller $u^r_{(S,m)}$ and buyer $u^r_{(B,m)}$ can be defined as follows:

$$u^r_{(S,m)} = \delta_S^{r-1} \cdot [z - P_S^m - TP_S^m - C_S(r)] \tag{12}$$

$$u^r_{(B,m)} = \delta_B^{r-1} \cdot [P_B^m - z - TP_B^m - C_B(r)] \tag{13}$$

where P_i^m, $i \in (B, S)$, is the value of message m to the player i. TP_S^m and TP_B^m are constants and denote the costs of transmitting and receiving, respectively. δ_i, $i \in (B, S)$, denotes the message forwarding capability of the player i. $C_S(r)$ and $C_B(r)$ are the costs of seller S and buyer B on the price of discussing the message m, respectively.

From formulas (12) and (13), we know the value of P_i^m is related to the size of the message m, the current virtual money and the selfishness of the nodes. Hence, for seller S, we define P_S^m as follows:

$$P_S^m = \rho_S \times m_s \times V_S \times SM_{i,j} \tag{14}$$

where $\rho_S \in (0, 1)$ is a price factor of the seller S. m_s is the size of the message m. V_S is the virtual money possessed by the seller S.

Similarly, for the buyer B , the P_B^m can be defined as

$$P_B^m = \rho_B \times m_s \times V_B \times SM_{j,i} \tag{15}$$

where $\rho_B \in (0, 1)$ is a price factor of the buyer B. m_s is the size of the message m. V_B is the virtual money possessed by the buyer B.

On the other hand, since δ_i denotes the message forwarding capability of the player i. Hence, we employ the total number of messages forwarded by nodes in a time period T to define δ_i.

$$\delta_S = \lambda_S . \frac{Q_{tot,S}}{T} \tag{16}$$

$$\delta_B = \lambda_B . \frac{Q_{tot,B}}{T} \tag{17}$$

where λ_S and λ_B are the message forwarding capability factors of the seller S and the buyer B, respectively.

Assuming that the cost of negotiating the price of message m is fixed ω every round. Then we have

$$C_S(r) = C_B(r) = r \cdot \omega \tag{18}$$

Based on formulas (12)–(18), we utilize the following method to illustrate the cause of selfishness.

Assuming that in the bargain game, the buyer B and seller S will eventually reach a trading price at most in round R. Then we analyze the transaction process backwards, starting from the last round, in this process, for the seller S, the best trading strategy is to always propose

假设 是这样的话

$$z = P_B^m - TP_B^m + C_S(R - r) \tag{19}$$

in round r. As the buyer B would like to maximize his own profit, he will accept the price

$$z \le P_B^m - TP_B^m + C_S(R - r) \tag{20}$$

in round r. According to Nash equilibrium [42,43], this strategy is a unique sub-game perfect Nash equilibrium, and the price reaches an agreement in the first round. Here, the sellers utility is

$$\begin{aligned} u^1_{(S,m)} &= z - P_S^m - TP_S^m - C_S(1) \\ &= P_B^m - TP_B^m - P_S^m - TP_S^m \end{aligned} \tag{21}$$

We assume that $P_B^m \geq TP_B^m + P_S^m + TP_S^m$. This is mainly because in the process of message forwarding, the price of the message will be increased when the message passes through a relay node, which is also in line with the reality of the scene.

The buyers utility is

$$\begin{aligned} u^1_{(B,m)} &= P_B^m - z - TP_B^m - C_B(1) \\ &= -C_S(1) - C_B(1) \\ &= -2\omega \end{aligned} \tag{22}$$

Besides, if the seller S and buyer B can not reach an agreement in the last round, then the utility function of seller S and buyer B are as follows:

$$\begin{aligned} u^{R'}_{(S,m)} &= -\delta_S^{R-1} \cdot C_S(R) \\ &= -\left(\lambda_S \cdot \frac{Q_{tot,S}}{T}\right)^{R-1} \cdot R \cdot \omega \end{aligned} \tag{23}$$

$$\begin{aligned} u^{R'}_{(B,m)} &= -\delta_B^{R-1} \cdot C_B(R) \\ &= -\left(\lambda_B \cdot \frac{Q_{tot,B}}{T}\right)^{R-1} \cdot R \cdot \omega \end{aligned} \tag{24}$$

Therefore, from formulas (22) and (24) we can see that the result is always unacceptable for the buyer B whether buyer B accepts the trading price or not. This explains why nodes are reluctant to forward messages for others, and it also explains the reason for the selfishness of the nodes.

To promote cooperation among nodes in the network, for the seller S, taking into account the interests of the buyer B, it is impossible to propose the bargain price in formula (19). Therefore, in the bargain game, there is a trading price Z that both the seller S and the buyer B are satisfied with it.

Theorem 1. *In the bargain game, there exists a unique sub-game perfect Nash equilibrium. According to Nash equilibrium, the deal ends in the first round with the following price:*

$$Z = \frac{(1-\delta_B)(P_B^m - TP_B^m) + (1-\delta_S)\delta_B(P_S^m + TP_S^m) + (4\delta_B - 3\delta_B\delta_S - 1)\omega}{1 - \delta_B\delta_S} \tag{25}$$

Proof. See Appendix. □

Theorem 1 shows that in message forwarding process, the transaction price of the message will be reached at the first time, which means that the seller S and the buyer B have more time to seek the next deal. When the price of the message is determined, the message will be forwarded to the relay node. Repeat this process until the destination node receives the message.

Finally, when the destination node N_d receives the message m, the CCC rewards each node who relays the message m according to the digital receipts. We assume that for each message forwarding, the sum of the maximum reward is C. In addition, when the destination node N_d receives the message m, we consider the importance $Pr_d^m(t+1)$ of the message m to the destination N_d at current $t+1$ moment is proportional to the rewards C_{tot} that all nodes can obtain. Thus, we can define C_{tot} as follows:

$$C_{tot} = Pr_d^m(t+1) \times C \tag{26}$$

In Han et al. [44], $Pr_d^m(t+1)$ can be obtained by iterative equation

$$Pr_d^m(t+1) = \frac{p_{id}(t)}{1 - (1 - p_{id}(t))^2} Pr_i^m(t) \tag{27}$$

where $Pr_i^m(t)$ is the importance of message m to node N_i in the time t slot. $p_{id}(t)$ is the probability that node N_i encounters node N_d in the time t slot, which can obtain by formula (3).

For each relay node N_j, we assume that the longer N_j carries the message m, the less reward he will get. Besides, if a relay node forwards the message directly to the destination node, accordingly, it should receive more reward. To illustrate this phenomenon conveniently, we assume that $\{N_1, N_2, \cdots, N_j, \cdots N_n\}$ is the forwarding sequence of message m, where N_1 and N_n are source and destination node, respectively. N_j denotes the $j-th$ carrier of the message m. We use the distance $|n-j|$ to describe the reward the relay node N_j can get. The bigger the value is, the less the reward. Based on the discussion, we can define the reward C_j of the relay node N_j as follows:

$$\begin{aligned} C_j &= \left(\tfrac{1}{n-1}\left(1 - \tfrac{t_j}{t-t_s}\right)\right) \times \left(\tfrac{1}{n-1}\left(1 - \tfrac{2|n-j|}{n(n-1)}\right)\right) \times C_{tot} \\ &= \tfrac{1}{(n-1)^2}\left(1 - \tfrac{t_j}{t-t_s}\right)\left(1 - \tfrac{2|n-j|}{n(n-1)}\right) \times C_{tot} \end{aligned} \tag{28}$$

where t_j is the time of the node N_j carrying the message m, t_s is the moment when the message m is generated, and t is the moment when the message is received by the destination node N_d (or N_n). In addition, $\sum_{j=1}^{n} t_j = t - t_s$.

From the formula (28), we can see if a message carrier quickly forwards the message to the next relay node or the destination node, then the message carrier will gain more profit. There is no doubt that such a reward mechanism will improve the efficiency of each node participating in message forwarding, which is important for maintaining the performance of the entire network.

4.3. Routing decision scheme

In OppNets, an efficient routing protocol can not only improve the success rate of message forwarding, but also reduce the cost of the network. To facilitate our expression below, we utilize C_{N_i} to represent the neighbour set of node N_i, and $C_{N_i}^m$ to represent the set of messages carried by node N_i. In our proposed routing algorithm (Algorithm 1), if a node N_i carrying a message m encounters a node

Algorithm 1 PRGT routing algorithm.

Begin:
1: for each $m \in C_{N_i}^m$ do
2:   for each $N_j \in C_{N_i}$ do
3:     if $N_d = N_j$ then
4:       N_i transmits m to N_j
5:     else
6:       if $m \notin C_{N_j}^m$ and $p_{i,i} < p_{i,j}$ then
7:         transmit m and generate $D_{i,j}^m$
8:       end if
9:     end if
10:   end for
11: end for
12: submit $D_{i,j}^m$ to CCC
13: if $m \in C_{N_d}^m$ then
14:   CCC provides rewards to N_i and N_j
15: end if
End.

N_j that has not the message m and has a higher probability of encountering the destination node N_d (Algorithm 1: line 6). Then the message m will be forwarded to the node N_j. Before the message is transmitted, the node N_i and the node N_j agree on the price of the message m by the formula (25). When the message m transmission is completed, the node N_i and the node N_j generate a digital receipt $D_{i,j}^m$ to record the transaction information (Algorithm 1: line 7). Then, when the two nodes connect the Internet, they submit

Table 1
Simulation setup.

Parameter	Default value
Transmission Speed	54 Mbps
Transmission Range	50 m
Message Size	0.5 MB - 1 MB
TTL	300 min
Message Interval	15 s–35 s
α	0.6
β	0.4
k	0.02
ϕ	0.5
φ	0.5

the digital receipt $D^m_{i,j}$ to the CCC, respectively (Algorithm 1: line 12). Finally, when the destination node N_d receives the message m, the CCC will reward the relay node N_j according to the formula (28) (Algorithm 1: line 14).

5. Performance evaluations

In this section, we use the Opportunistic Network Environment (ONE) simulator to evaluate our proposed routing algorithm (PRGT). In our simulation, we use the INFOCOM05 dataset and INFOCOM06 dataset to simulate the generation and sending process of messages. The INFOCOM05 dataset contains 43 users equipped with a wireless device for collecting the connection information in a period of 274,883 seconds. Similarity, the INFOCOM06 includes 97 users, and each user is also equipped with a wireless device for collecting the connection information in a period of 342,915 seconds. Besides, the source and destination node are randomly selected from the dataset. Some common simulation settings are shown in Table 1.

We compare our proposed routing algorithm with some classical routing algorithms, including Epidemic, SprayAndWait and Prophet via the following three different metrics:

- *Delivery Ratio*: The ratio of messages that have been delivered to the destination nodes to the messages generated by the source nodes. The delivery ratio reflects the impact of routing on network performance.
- *Average Delivery Latency*: The average time duration from messages are generated until received by destination nodes.
- *Overhead Ratio*: The ratio of the total number messages created by source nodes to the total number messages forwarded by all nodes.

5.1. Impact of different percentage of selfish nodes on routing performance

In this section, we compare PRGT routing algorithm with some classical routing algorithms under different percentage of selfish nodes. In our experiments, we consider two types of nodes: selfish nodes and normal nodes. For the former, they are not fully cooperative, and only forward messages generated by themselves and their friends. For the latter, they are willing to participate in all messages forwarding for others. Besides, in order to eliminate the impact of buffer size and energy, we assume that each node has enough space to store messages they receive and the bandwidth is large enough to exchange all messages between nodes in encountering times. In terms of todays communication technology, these assumptions are reasonable. Moreover, we use the real data set to simulate a real opportunity network scenario. We assume that each node has its own trajectory. With this mind, we use the shortest path model in our simulation.

Fig. 1(a) shows that the delivery ratio of all algorithms decreases with different percentage of selfish nodes, because the more the selfish nodes, the more packets will be dropped. Selfish nodes cannot be transformed in Epidemic, SprayAndWait and Prophet, so their delivery ratio reduces more quickly than PRGT. Compared with Epidemic, SprayAndWait and Prophet, the delivery ratio of PRGT decreases by 11.29%, which is lower than 21.82% of Epidemic, 23.48% of Prophet and 18.51% of SprayAndWait when selfish nodes increase from 0 to 90%. Obviously, in terms of delivery ratio, PRGT is better than the other three routing algorithms. In PRGT, we use game theoretic model to facilitate each selfish node to participate in the forwarding of messages. In the process of message forwarding, participants can maximize their own interests. In the other three routing algorithms, since there is no effective solution to handle selfish nodes, selfish nodes refuse to forward messages for non-friends nodes. As a result, PRGT works better in facing selfish nodes and has a higher delivery ratio.

Fig. 1(b) shows the comparison of average latency. From the figure, we can infer that when the percentage of selfish nodes is more than 20%, PRGT has the lowest average delay. Since the Epidemic is a flooding based routing algorithm, when the percentage of selfish node is lower than 20% Epidemic has the lowest average delay. But when the percentage of selfish nodes is more than 50%, Epidemic has the highest average delay. In Prophet and SprayAndWait routing algorithms, the message carriers have to wait for a cooperative node for forwarding messages, thus, they also have a long delay.

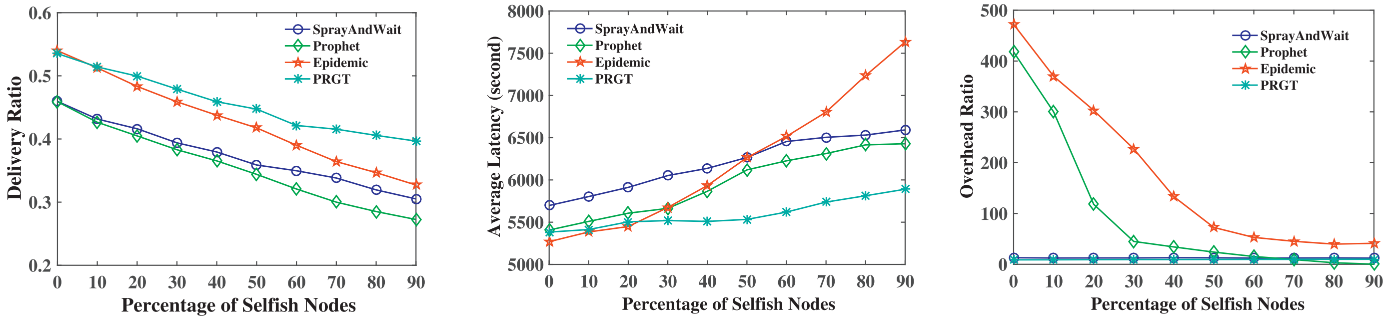
Fig. 1(c) shows the overhead ratio by comparing the PRGT with other three algorithms. As expected, the overhead ratio of Epidemic and Prophet decrease with the percentage of selfish node. However, PRGT and SprayAndWait have a relatively stable overhead ratio. In Epidemic, when the number of selfish nodes increases in the network, the carrier of the same message will be reduced, correspondingly. As a result, the overhead ratio decreases, but it still has the highest overhead ratio. In SprayAndWait, each message has a fixed number of copies, thus, it can keep a stable overhead ratio even when the selfish nodes increase in the network. Compared with the other three algorithms, when the percentage of selfish nodes more than 60%, Prophet has the lowest overhead ratio. But in this case, it is difficult to find a suitable relay node, as shown in Fig. 1(a), its delivery ratio is the lowest under this circumstance. For PRGT, in the process of message forwarding, the carrier can choose a suitable relay node through game theory model, which can not only improve the delivery ratio, but also keep a low overhead ratio.

In simulations with INFOCOM05 dataset (Fig. 2), our proposed routing scheme PRGT has a better delivery ratio, but it also has low average latency and overhead ratio compared with Epidmic, SpayAndWait and Prophet. The result is similar to the result of using the INFOCOM06 dataset (in Fig. 1). Therefore, we can see that both the dense network and sparse network, our proposed PRGT routing algorithm presents a better routing performance.

5.2. Impact of different buffer size of nodes

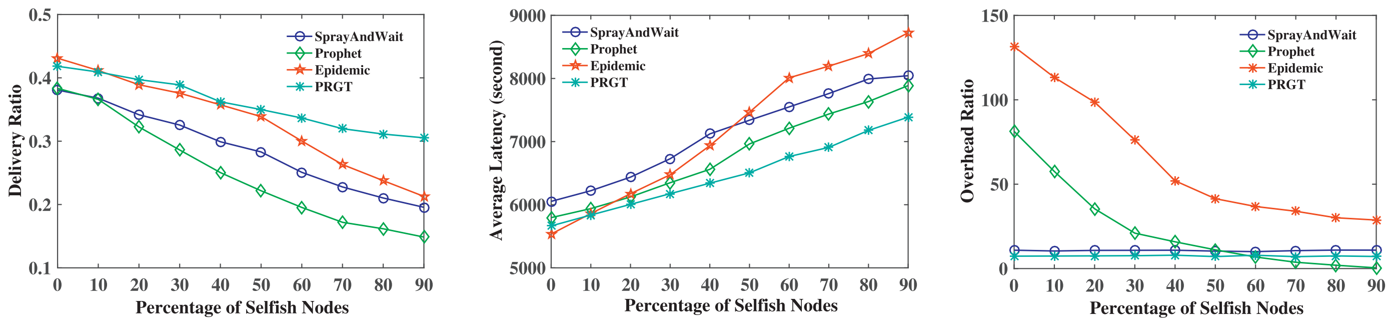
In this section, we consider the impact of energy and buffer size on delivery ratio, average latency and overhead ratio, respectively. Although we assume that the energy and buffer size of nodes are adequate in the previous part of the simulation, it is meaningful to consider the impact of buffer size on network performance. In the experiment, we set the percentage of selfish nodes to 40% and vary the buffer size of the node from 10 MB to 100 MB. Some of the other settings are the same as the previous part of the experiment.

From the Fig. 3(a), we can see that with the increase of buffer size, the delivery ratio of all four routing algorithms increases accordingly. When the buffer size is small, more copies of the message will be discarded, so the delivery ratio is also very low. In PRGT, when the resources(buffer size, energy) are limited, we employ probabilistic prediction model based on the Markov chain to



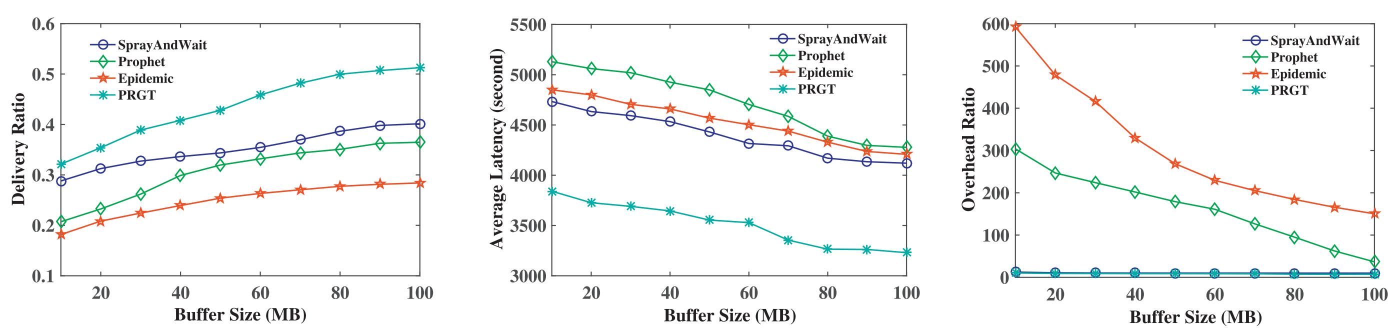
(a) (b) (c)

Fig. 1. Comparison of algorithms using INFOCOM06 data set. (a) Delivery Ratio vs. Percentage of Selfish Nodes. (b) Average Latency vs. Percentage of Selfish Nodes. (c) Overhead Ratio vs. Percentage of Selfish Nodes.



(a) (b) (c)

Fig. 2. Comparison of algorithms using INFOCOM05 data set. (a) Delivery Ratio vs. Percentage of Selfish Nodes. (b) Average Latency vs. Percentage of Selfish Nodes. (c) Overhead Ratio vs. Percentage of Selfish Nodes.



(a) (b) (c)

Fig. 3. Comparison of algorithms using INFOCOM06 data set. (a) Delivery Ratio vs. Percentage of Selfish Nodes. (b) Average Latency vs. Percentage of Selfish Nodes. (c) Overhead Ratio vs. Percentage of Selfish Nodes.

select the appropriate relay nodes, and use game theory model to reduce the impact of selfish nodes, so the delivery ratio of PRGT is highest. Compared with PRGT, the other three routing algorithms do not have the mechanism of dealing with selfish nodes and the section of relay nodes is blind (except Prophet), therefore, the delivery ratio is relatively lower.

Fig. 3(b) shows the comparison of average latency under different buffer size. Although the average latency of all four routing algorithms is gradually decreased when the buffer size of nodes increases, the PRGT has the least average latency. For any node in the network, the larger the buffer size, the more copies of different messages can be retained, and the lower the average delay. In Prophet, the carriers have to wait for the cooperation nodes (friend nodes or normal nodes) and higher probability nodes for messages forwarding, so the average latency is highest. Similarly, in Epidemic and SprayAndWait, the carriers also need to wait for a cooperative relay node, which increases the latency of message forwarding.

In Fig. 3(c), we can see that the overhead ratio of PRGT routing scheme is similar to SprayAndWait and much lower than that of Epidemic and Prophet. In SprayAndWait, the copies of any messages are fixed, so the overhead ratio is also very low. Since Epidemic is a routing based on flooding, there is no doubt that the overhead ratio is highest among the other routing algorithms.

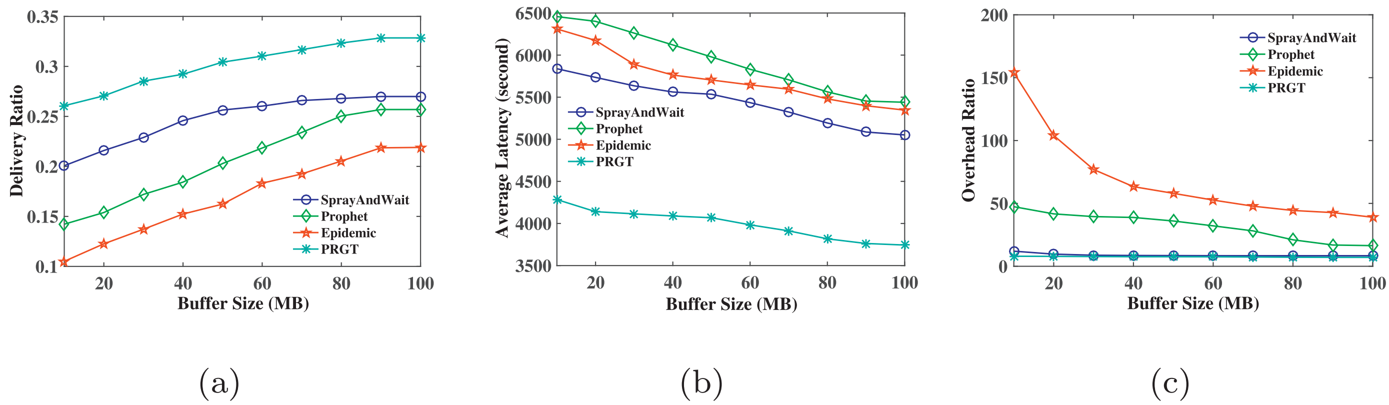


Fig. 4. Comparison of algorithms using INFOCOM05 data set. (a) Delivery Ratio vs. Percentage of Selfish Nodes. (b) Average Latency vs. Percentage of Selfish Nodes. (c) Overhead Ratio vs. Percentage of Selfish Nodes.

Similarly, when we use the INFOCOM05 dataset (in Fig. 4), we obtain the same results as using the INFOCOM06 dataset (in Fig. 3). With the buffer size changing from 10 M to 100 M, our proposed routing scheme PRGR has better performance than Epidemic, SprayAndWait and Prophet.

6. Conclusion

In this paper, we have designed a Probabilistic Routing scheme based on Game Theory for OppNets. In the process of message forwarding, we use game theory model to promote cooperation among selfish nodes. For each node in the network, it can obtain more profits by forwarding messages, which is beneficial for improving the enthusiasm of them to participate in message forwarding. Simulation results show that our proposed routing scheme PRGT has a great performance in delivery ratio, average latency and overhead ratio compared with Epidemic, Prophet and SprayAndWait. Our results also verify the effectiveness and correctness of our proposed algorithm. 帮派欺骗赏金

In the future work, we will further study how to find and solve the problem of gangs defrauding the bounty. Such a problem can be described by a simply example as follows: In the network, nodes A, B and C are a team, in the message forwarding process, node A forwards the message generated by itself to node B, and node B forwards the message to the destination node D. Such message forwarding is a complete process, so in the incentive routing scheme, if the process continues, then the team can always defraud the reward, which obviously does not help improve the performance of the network. Therefore, how to find and solve such fraudulent gangs is one of the key research contents of our future work. On the other hand, we will continue to study how to use game theory to solve malicious and aggressive nodes in the network.

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Appendix

Proof of Theorem 1

We utilize the backward induction method to prove a sub-game Nash perfect equilibrium. As the bargain game is infinitely repeated, it's difficult to find a starting point for backward induction. However, there should exist a sub-game perfect Nash equilibrium in the bargain game, where the seller S offers a price z^* and the buyer B accepts it in the first round. Similarly, if the bargain game was from the third round, the seller S offers the z^* and the buyer B accept it. Therefore, the infinitely repeated bargain game can be considered as a bargain game with three rounds to get the equilibrium.

Now, we analyze the bargain game process from round 3, in this round, the seller S offers a price z^* and the buyer accepts B it. Next, in round 2, the buyer B offers a price z_2, and the seller S accepts the price z_2 only when

$$\begin{aligned}
&u^2_{(S,m)} \geq u^3_{(S,m)} \\
&\delta_S \cdot \left[z_2 - P^m_S - TP^m_S - 2\omega\right] \geq \delta^2_S \cdot \left[z * -P^m_S - TP^m_S - 3\omega\right] \\
&z_2 \geq P^m_S + TP^m_S + 2\omega + \delta_S \cdot \left[z * -P^m_S - TP^m_S - 3\omega\right] \\
&= \sigma_1
\end{aligned} \tag{29}$$

Then, the buyer B put forward a price z^*_2 that maximizes its utility. Therefore

$$\begin{aligned}
&z^*_2 \\
&\quad = \arg\max_{z_2} (u^2_{(B,m)}) \\
&\quad = \arg\max_{z_2} \begin{cases} \delta(P^m_B - z_2 - TP^m_B - C_B(2)) & z_2 \geq \sigma_1 \\ u^3_{(B,m)} & z_2 < \sigma_1 \end{cases} \\
&\quad = \sigma_1
\end{aligned} \tag{30}$$

Next, move the first round, the seller S put forward a price z_1 and the buyer B accept the price only when

$$\begin{aligned}
&u^1_{(B,m)} \geq u^2_{(B,m)} \\
&P^m_B - z_1 - TP^m_B - C_B(1) \geq \delta_B\left[P^m_B - z^*_2 - TP^m_B - C_B(2)\right] \\
&z_1 \leq P^m_B - TP^m_B - C_B(1) - \delta_B\left[P^m_B - z^*_2 - TP^m_B - C_B(2)\right] \\
&= \sigma_2
\end{aligned} \tag{31}$$

Then, the seller S offers a price z^*_1 that maximizes its utility. Hence,

$$\begin{aligned}
&z^*_1 \\
&\quad = \arg\max_{z_1} (u^1_{(S,m)}) \\
&\quad = \arg\max_{z_1} \begin{cases} z_1 - P^m_S - TP^m_S - C_S(1) & z_1 \geq \sigma_2 \\ u^2_{(B,m)} & z_1 < \sigma_2 \end{cases} \\
&\quad = \sigma_2
\end{aligned} \tag{32}$$

As the infinite repeated equilibrium process is equal to three rounds of the equilibrium process. Thus, we can obtain

$$z_1^* = z^*$$
$$P_B^m - TP_B^m - \omega - \delta_B[P_B^m - z_2^* - TP_B^m - 2\omega] = z^*$$
$$z^* = \frac{(1-\delta_B)(P_B^m - TP_B^m) + (1-\delta_S)\delta_B(P_S^m + TP_S^m) + (4\delta_B - 3\delta_B\delta_S - 1)\omega}{1-\delta_B\delta_S}$$

This completes our proof. □

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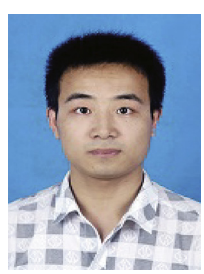

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